Askada: A Transparent Conversational Agent for Early-Stage Academic Research

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Askada is a transparent conversational agent that helps first-year students refine research topics and find authoritative sources. To address the lack of trust and accountability in general-purpose AI, Askada features an explainable recommendation process and an auditable trail for instructor oversight. An autobiographical evaluation across four task scenarios demonstrates that Askada outperforms baseline tools in delivering structured, verifiable scholarly information. Our findings highlight the potential of lightweight, transparent interfaces to support novice researchers while promoting academic integrity in AI-enhanced learning environments.

CCS CONCEPTS • Human-centered computing • Human computer interaction (HCI); Information systems • Information retrieval

Additional Keywords and Phrases: Conversational agents, Technology-enhanced learning, Explainable AI

ACM Reference Format:

Ruochen Zhao, Sangeun Han, Nibras Ar Rakib, Qianru Shi, and Javed Mostafa. 2026. Askada: A Transparent Conversational Agent for Early-Stage Academic Research. In Joint Proceedings of the ACM IUI Workshops (TRUST-CUA@IUI '26), March 23–26, 2026, College Station, TX, USA. ACM, New York, NY, USA, 4 pages. NOTE: This block will be automatically generated when manuscripts are processed after acceptance.

1 INTRODUCTION

The use of agents for academic tasks has grown quickly over the past few years. This is due to the ongoing development of different generative AI models [3]. While these agents improve interactive learning [1, 17], they still have difficulty helping students with research at the beginning stages [5]. Novice students often find it hard to pinpoint a clear topic for their assignments. They frequently receive responses that lack trustworthy, reliable, or scholarly resources [7]. These issues make it challenging for early-stage students to grasp why certain topics appear, how to refine them, and whether the suggestions from typical conversational agents meet actual academic expectations.

1.1 PROBLEM STATEMENT

Freshmen often struggle to transform vague initial ideas into structured, researchable topics. While traditional chatbots offer fluent interaction, they frequently lack the academic rigor, structural depth, and credibility required for scholarly work, making it difficult for novice learners to develop focused research directions. Consequently, a primary challenge lies in designing a conversational agent that provides structured assistance and topic variations while remaining accessible to students at the earliest stages of their research. Furthermore, many AI tools generate recommendations without revealing their sources or reasoning, hindering a student's ability to verify information. In academic settings, transparency is essential; students must understand how outputs are derived and where information originates. Askada addresses this by integrating explainable reasoning, transparent API usage, and an auditable interaction trail into a single workflow that supports instructor oversight. Beyond these design goals, this demo also investigates how specific interaction tasks, such as error recovery and query clarification, shape the user experience in resolving ambiguity and refining vague research concepts.

2 RELATED WORK

Past work in information-seeking shows that freshman searchers often experience uncertainty and difficulty while defining research questions, as they often move iteratively through exploration and interpretation stages before gaining clarity [10, 15]. Traditional keyword-based tools further impede this process by offering ranked results without supporting query refinement, which leads to incomplete or inefficient search sessions [19]. More interactive systems allowing query adjustment and incremental search through "berry-picking" behaviors [2] have been shown to improve planning and review during exploratory search [13, 14]. Meanwhile, research on AI-anchored educational tools highlights both the potential for accelerated information access and persistent issues such as vague feedback, unverified references, and limited support for further conceptual learning [4, 6, 8]. Recent analyses of large language models also reveal challenges regarding reliability and reference authenticity in academic contexts [9, 18]. These findings indicate a need for conversational agents that not only assist with topic formulation but also provide transparent reasoning, authentic scholarly sources, and traceable workflows.

3 ASKADA

Askada is a WhatsApp-based conversational agent designed to minimize cognitive load by leveraging students' familiar communication channels. Grounded in Minimum Dictionary Language (MDL) principles [11], the system employs an explanatory, menu-driven interaction model to facilitate topic articulation and scholarly resource retrieval. By integrating these principles, Askada provides a structured, predictable environment that supports novice researchers in identifying authoritative resources and developing initial research guidelines. To foster trust and accountability, Askada prioritizes transparency through a visible planning process and an auditable interaction history. Furthermore, every interaction is timestamped and logged, enabling the export of an audit trail for instructor oversight. This combination of transparent reasoning, verifiable sources, and traceable workflows ensures that Askada provides a more controllable and trustworthy alternative to general-purpose AI tools. A video demonstration of Askada has been created at: https://youtu.be/QA8LQKyrNMo.

4 EVALUATION METHOD

Following an autobiographical design approach [12], Author 1 compared Askada against a baseline of ChatGPT 5.1. Performance was measured by completion time, interaction steps, topic clarity, and reference authenticity [16]. The evaluation covered four scenarios: (T1) Narrowing Vague Topics, (T2) Ambiguity Resolution, (T3) Error Recovery, and (T4) Source Transparency. This setup directly assesses Askada's ability to handle the uncertainty and technical errors common in early-stage research.

5 RESULTS

Structured walkthroughs revealed that Askada produces more grounded topic formulations compared to the baseline's fluent but unverified suggestions. Specifically, Askada ensures source authenticity via live API metadata (T4), whereas ChatGPT generates only approximate citations. In error-input scenarios (T3), Askada's proactive clarification prompts allowed for successful query reconstruction, whereas the baseline relied on "best-guess" definitions. While these formative results are lab-based, they demonstrate Askada's ability to tackle early-stage research challenges through transparency and recovery. Future work will involve a formal user study with undergraduate students to measure trust and explainability.

Table 1: Comparison of Task Handling Between ChatGPT 5.1 and Askada

Task	User Input	Baseline (ChatGPT 5.1)	Askada
T1: Narrowing Vague Topics	More <digital privacy>	Provide 5 general sub-topics line-by-line.	Delivers the entire structured response at once.
T2: Ambiguity Resolution	More <privacy issues>	Provides a standard list of issues without guidance on next steps	Provides definitions followed by a command menu (e.g., article <N>, book <N>) to guide further search.
T3: Error Recovery	Mor Privacy concernt	Automatically fixes "mor" and "concernt" to provide a definition immediately.	Identifies unknown command; asks: "Did you mean more <privacy concern>" to confirm user intent.
T4: Source Transparency	Article <digital privacy>	Admits no direct API access.	Retrieves real-time citations from scholars Portal, Web of Science, Scopus with DOIs and readability levels.

6 FUTURE WORK

Our next step is to evaluate Askada in depth with undergraduate students to assess its impact on trust, explainability, and a clear understanding of system limitations. We plan to move beyond autobiographical and lab-based assessments by using complete user evaluation with a wider participant group drawn from early-stage students. Future development will also enhance workflow-trace features for instructors and support more recovery and planning functions to further boost Askada's transparency and accountability.

7 CONCLUSION

This demo showcased an updated version of Askada which supports clear topic formulation, disambiguation, error recovery, and source transparency. Through the four structured tasks, we showed how these features can make early-stage research more understandable and manageable for novice students. Together, these elements demonstrate how lightweight agents like Askada can enhance trust, predictability, and oversight in academic topic-identification processes.

REFERENCES

[1] David BaiDoo-Anu and Leticia Owusu Ansah. 2023. Education in the Era of Generative Artificial Intelligence (AI): Understanding the Potential Benefits of ChatGPT in Promoting Teaching and Learning. *Journal of AI* 7, 1 (December 2023), 52–62. https://doi.org/10.61969/jai.1337500

[2] Marcia J. Bates. 1989. The design of browsing and berrypicking techniques for the online search interface. *Online Review* 13, 5 (May 1989), 407–424. https://doi.org/10.1108/eb024320

[3] Staphord Bengesi, Hoda El-Sayed, Md Kamruzzaman Sarker, Yao Houkpati, John Irungu, and Timothy Oladunni. 2024. Advancements in Generative AI: A Comprehensive Review of GANs, GPT, Autoencoders, Diffusion Model, and Transformers. *IEEE Access* 12, (2024), 69812–69837. https://doi.org/10.1109/ACCESS.2024.3397775

[4] Aras Bozkurt. 2023. Unleashing the Potential of Generative AI, Conversational Agents and Chatbots in Educational Praxis: A Systematic Review and Bibliometric Analysis of GenAI in Education. *Open Praxis* 15, 4 (November 2023), 261–270. https://doi.org/10.55982/openpraxis.15.4.609

[5] Kiroong Choe, Seokhyeon Park, Seokweon Jung, Hyeok Kim, Ji Won Yang, Hwajung Hong, and Jinwook Seo. 2024. Supporting Novice Researchers to Write Literature Review using Language Models. In *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*, May 02, 2024. ACM, Honolulu HI USA, 1–9. https://doi.org/10.1145/3613905.3650787

[6] Chris Dede, John Richards, and Bror Saxberg (Eds.). 2018. *Learning Engineering for Online Education: Theoretical Contexts and Design-Based Examples* (1st ed.). Routledge. https://doi.org/10.4324/9781351186193

[7] Fan Gao, Hang Jiang, Rui Yang, Qingcheng Zeng, Jinghui Lu, Moritz Blum, Tianwei She, Yuang Jiang, and Irene Li. 2024. Evaluating Large Language Models on Wikipedia-Style Survey Generation. In *Findings of the Association for Computational Linguistics ACL 2024*, 2024. Association for Computational Linguistics, Bangkok, Thailand and virtual meeting, 5405–5418. https://doi.org/10.18653/v1/2024.findings-acl.321

[8] Wayne Holmes, Maya Bialik, and Charles Fadel. 2023. Artificial intelligence in education. In *Data ethics : building trust : how digital technologies can serve humanity*, Christoph Stückelberger and Pavan Duggal (eds.). Globethics Publications, 621–653. https://doi.org/10.58863/20.500.12424/4276068

[9] Lei Huang, Weijiang Yu, Weitao Ma, Weihong Zhong, Zhangyin Feng, Haotian Wang, Qianglong Chen, Weihua Peng, Xiaocheng Feng, Bing Qin, and Ting Liu. 2025. A Survey on Hallucination in Large Language Models: Principles, Taxonomy, Challenges, and Open Questions. *ACM Trans. Inf. Syst.* 43, 2 (March 2025), 1–55. https://doi.org/10.1145/3703155

[10] Carol C. Kuhlthau. 1991. Inside the search process: Information seeking from the user's perspective. *J. Am. Soc. Inf. Sci.* 42, 5 (June 1991), 361–371. https://doi.org/10.1002/(SICI)1097-4571(199106)42:5%253C361::AID-ASI6%253E3.0.CO;2-%2523

[11] Javed Mostafa, Xiaopeng LU, and Sandeep Avula. 2024. Methods, systems, and computer readable media for creating and using minimum dictionary language (MDL) to access data in closed-domain data sets. Retrieved October 21, 2025 from https://patents.google.com/patent/US12026482B2/en

[12] Carman Neustaedter and Phoebe Sengers. 2012. Autobiographical design in HCI research: designing and learning through use-it-yourself. In *Proceedings of the Designing Interactive Systems Conference*, June 11, 2012. ACM, Newcastle Upon Tyne United Kingdom, 514–523. https://doi.org/10.1145/2317956.2318034

[13] Kimeya Orin and Orland Hoeber. 2025. Organizing Found Information in Public Digital Library Search. In *Proceedings of the 2025 ACM SIGIR Conference on Human Information Interaction and Retrieval*, March 24, 2025. ACM, Melbourne Australia, 358–366. https://doi.org/10.1145/3698204.3716471

[14] Mohammad Hasan Payandeh, Orland Hoeber, Miriam Boon, Dale Storie, and Veronica Ramshaw. 2025. A study of drag-and-drop query refinement and query history visualization for mobile exploratory search. *Asso for Info Science & Tech* 76, 6 (June 2025), 848–866. https://doi.org/10.1002/asi.24977

[15] Linda Schamber and Gary Marchionini. 1996. Information Seeking in Electronic Environments. *Journal of Education for Library and Information Science* 37, 1 (1996), 81. https://doi.org/10.2307/40324289

[16] Ben Shneiderman and Catherine Plaisant. 2005. *Designing the user interface: strategies for effective human-computer interaction* (4. ed., internat. ed ed.). Pearson/Addison-Wesley, Boston, Mass. Munich.

[17] Aniella Mihaela Vieriu and Gabriel Petrea. 2025. The Impact of Artificial Intelligence (AI) on Students' Academic Development. *Education Sciences* 15, 3 (March 2025), 343. https://doi.org/10.3390/educsci15030343

[18] William H. Walters and Esther Isabelle Wilder. 2023. Fabrication and errors in the bibliographic citations generated by ChatGPT. *Sci Rep* 13, 1 (September 2023), 14045. https://doi.org/10.1038/s41598-023-41032-5

[19] Ryen W. White and Resa A. Roth. 2009. *Exploratory Search: Beyond the Query—Response Paradigm*. Springer International Publishing, Cham. https://doi.org/10.1007/978-3-031-02260-9